Data Analytics Methodology for Monitoring Quality Sensors and Events in the Barcelona Drinking Water Network

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Abstract

Water quality management is a key area to guarantee drinking water safety to the citizens. This task is based on disinfection techniques, such as chlorination, applied to the drinking water network to prevent the growing of microorganisms present in the water. The continuous monitoring of water quality parameters is fundamental to assess sanitary conditions of the drinking water and to detect unexpected events. The whole process is based on the assumption that the information retrieved from quality sensors is totally reliable. But due to the complexity of the calibration and maintenance of these chemical sensors, several factors affect the accuracy of the raw data collected. Consequently, any decision might be based on a non solid base. Therefore, this work presents a data analytics monitoring methodology based on temporal and spatial models to discover if a sensor is detecting a real change on water quality parameters or actually is providing inconsistent information due to some malfunction. The methodology presented, anticipated in 12.4 days, on average, the detection of a sensor problem before the fault was reported by the water utilities (WU) expert using knowledge accumulated with visual analysis. The proposed methodology has been satisfactorily tested on the Barcelona Drinking Water Network.

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1. Introduction

One of the main tasks of the water utilities (WU) is to transport and supply drinking water to the citizens throughout water distribution systems (WDS). Two of the WU's main areas concerned are: On the one hand, the operations department to manage the hydraulic infrastructure (e.g. pumping stations, reservoirs, pipes,...), and on the other hand, the water quality control department to manage the drinking water safety. Furthermore, different legal frameworks regulates the quality of drinking water to supply.

Water quality monitoring and control management programmes involve several tasks. As detailed in Bartram et al. (1996), such tasks are monitoring network design (e.g. which parameters to be measured, how often, etc.), laboratory work (e.g. chemical analysis, laboratory tests, etc.) and analytical quality assurance (e.g. production of reliable data) among other elements.

There are several techniques to treat the water in WDS and keep it healthy for human consumption. One common disinfection technique is the chlorination of water. This process consists in injecting chlorine or derivatives in the water. The injected chlorine is consumed (i.e. chemical reaction) in the WDS because of two main factors (Powell et al., 2000). On the one hand, due to reactions in the bulk water as e.g. by the presence of organic content in the water, by decay of the initial chlorine concentration because of the physical conditions (e.g. temperature). On the other hand, the chlorine reacts at the pipe wall, known as biofilm (a group of microorganisms adhered to the pipes' surface).

The chlorine in the water drops exponentially as follows:

$$C(t) = C_0 \cdot e^{-kT} \tag{1}$$

where $C(t)$ is the chlorine concentration (mg/l) at the instant t, C_0 is the initial chlorine concentration and T the time interval since the injection.

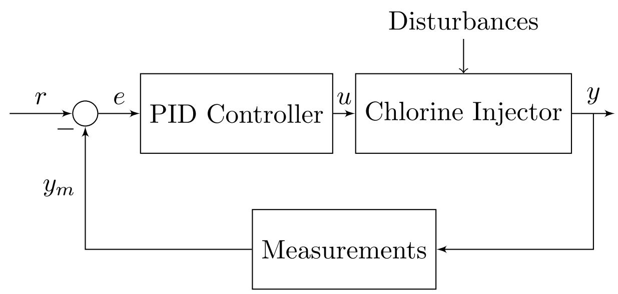

Figure 1: Chlorine injection process.

Thus, in order to keep residual chlorine in the water distribution network after a certain time T, it is necessary to inject a certain chlorine dose C_0. The chlorine injection, usually done in the reservoirs, regulated by an automatic controller, where a feedback control loop (typically based on a proportional-integral-derivative controller), depicted in Figure 1, injects a quantity of chlorine u determined by the error e between the concentration reference r and the measured chlorine concentration y_m.

The WU monitors the water quality parameters with on-line water quality sensors (multi-parametric and single-parametric) installed along the water transport and distribution networks. The most common water quality parameters monitored on-line are conductivity, temperature, pH and chlorine. Other interesting parameters such as total organic carbon (TOC) are well-known indicators of water quality. Moreover, laboratory analyses of water samples taken from different points of the network are essential to analyze biological and chemical components unobserved by the on-line sensors, or even to contrast them against on-line observations.

Quality sensors require a specific calibration planning prescribed by the manufacturer depending on the sensor's model to guarantee the reliability of the observations. Moreover, a preventive maintenance planning (e.g. bimonthly or quarterly) is also specified by the manufacturer to preserve data reliability.

Even though applying a preventive planning, these quality sensors could be affected by several problems such as the ones listed in Table 1. Thus, a corrective planning is always required to solve these unexpected problems affecting the sensors reliability.

Table 1: Main factors affecting the information gathered from water quality sensors.

Cause	**Consequence**
Communications problem	Data gap
Loss of sensitivity	Flat signal or slow drift down
Electronic malfunction	Noise and peaks in the signal
Miscalibration of the sensor	Offsets affecting the real value

There is significant research to detect and avoid intended and unintended injection of hazardous substances in the water distribution network to guarantee the drinking water safety. Several works have studied this particular subject in order to detect water contamination events. In Byer and Carlson (2005), different contaminants introduced in tap water are detected measuring pH, turbidity, conductivity, total organic carbon and chlorine and establishing as detection limits a threshold based on three time the standard deviation above the average of each magnitude. In Hou et al. (2014), a probabilistic principal component analysis (PPCA) method using UV-Vis spectrometers is detailed to detect contaminant injection into WDS. In Eliades et al. (2014), a model-based approach considering the chlorine input injection is used to compute bounds to compare with the sensors measurements. In Hall et al. (2007), a benchmark of a set of sensors from different manufacturers measuring distinct quality parameters is presented allowing to analyze and compare the sensitivity on the presence of various contaminants. In Hart et al. (2011), operational data and water quality are combined to reduce false positives rate in the quality event detection. In Ba and McKenna (2015), different change-point detection algorithms are applied to the residuals of an autoregressive model. Sensor placement is also an important topic to improve quality monitoring meanwhile reducing operational costs as discussed in Rathi and Gupta (2014). The hydraulic model and a simulation software are proposed in Nejjari et al. (2012) to detect and localize water quality abnormal parameters in the WDS.

Model-based approaches, such as Eliades et al. (2014) and Nejjari et al. (2012), have the main drawback that the performance depends directly on the water network model's accuracy. Moreover, due to the complex behaviour of the water parameters, it is unfeasible to develop an accurate physical model to describe the water quality dynamics. Hence, data-driven approaches are very interesting in this case and therefore widely used.

In addition, a major drawback, in general, of the existing approaches to detect drinking water quality events is that are based on the assumption that data gathered from these sensors are accurate and precise. But as we have pointed out, raw data from quality sensors could not be ready to be analyzed or to extract solid conclusions. Unreliable water quality information is a serious problem for the WU in order to guarantee a water supply that assures the citizens health.

Hence, the main motivation of this work is to provide a data analytics methodology for monitoring quality sensors and events applicable to drinking water networks, such as the mentioned before.

The contributions of this work are twofold. On the one hand, this work provides a methodology to get a solid information basis, discarding unreliable data, to improve decision making of the WU in the water quality management. On the other hand, a set of indicators are provided allowing to improve the preventive planning reducing the number of expensive corrective actions.

This work is focused on the application of the proposed methodology to solve the problem of quality events and unreliable sensors detection in a real WU with on-line monitored water quality parameters. In particular, the proposed methodology has been satisfactorily tested on the Barcelona drinking water network.

2. Case Study

The case study, used to illustrate the proposed methodology for monitoring quality sensors and events, is based on the Barcelona drinking water network. The Barcelona drinking water network is a complex WDS of over 4,600 km that supplies drinking water to 218 demand sectors. In this WDS, there are installed thousands of sensors along the network to know with precision the hydraulic state of the network to control and manage it efficiently. In addition, there are installed quality sensors and analysers to handle the water quality control.

For illustrative purposes, this paper is focused on the part depicted in Figure 2. The water supply of this zone can come from two different water sources: the rivers Ter and Llobregat. This part has been carefully selected with the help of the managers of the network since it presents the typical issues affecting the whole network.

The tank collects water to satisfy the three demand sectors. A chlorination process is continuously done in this tank based on an actuator (chlorine injection), a chlorine analyzer and some reference given by the WU's operators. At the entrance of each demand sector, a multi-parameter water quality sensor is installed to monitor and control the quality of the supplied water.

The WU collects hourly observations from multi-parameter sensors and 15-minutes observations from chlorine analyzers. The parameters observed are: temperature, conductivity, pH and chlorine. The single-parameter sensors measure chlorine.

The water quality data collected are analyzed by the experts using a visualization software to check any existing quality event or sensor problem. Another software system allows the experts to contrast field samples analyzed in the laboratory against the data collected from the sensors.

The methodology presented next has been inspired on the knowledge of the experts used to analyze, check and even forecast problems in the water quality system.

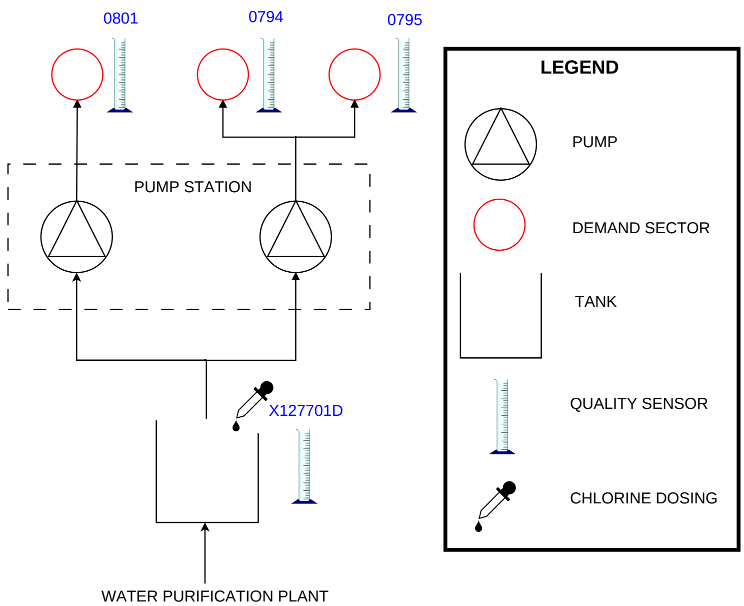

Figure 2: *Water Demand Sector* from the Barcelona Water Network.

3. Methodology

The methodology described in this section describes and analyzes the procedure followed to obtain a robust decision regarding the two monitoring objectives. As we discussed before, the first objective is to detect changes in the water quality parameters that can compromise the safety of the water supplied, and the second objective is to discriminate if the problem detected is a real change in the water quality parameters or whether it has been generated by unreliable observations due to some of the problems presented in Table 1.

3.1. Data pipeline

The methodology is based on a data pipeline of four steps, depicted in Figure 3. These steps are divided in two blocks by a dashed line: on-line and off-line. The training and validation stages are required to initialize and calibrate the models with historical data. Once the models are calibrated the on-line stages are able to process, computationally efficiently, new incoming

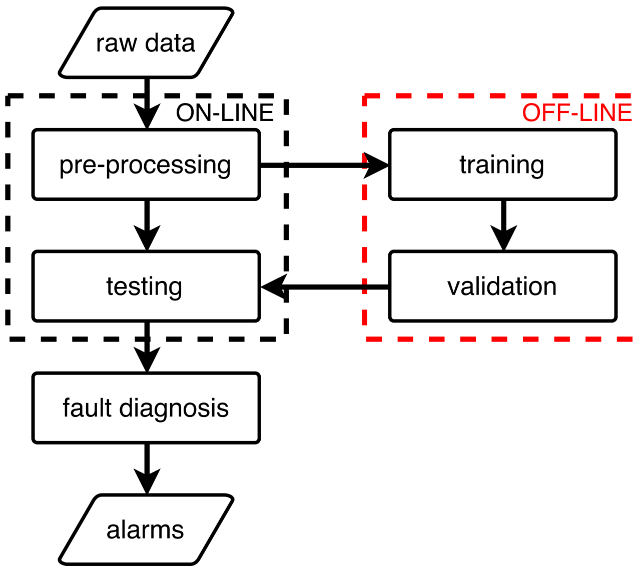

Figure 3: Data pipeline

data streams. Firstly, a *pre-processing* stage prepares and cleans the raw data: remove the noise, remove outliers establish a regular sampling time and apply some transformations (differencing and standardizing). Then, a *training* stage builds the models of the methodology detailed next using a given training data set, in order to characterize the normal state of the system. Using these models, a *validation* stage is executed on an independent data set (validation data set) to quantify the fitness of the models to the real behaviour and to determine the thresholds of the models.

Finally, the *testing* stage runs the models on a test data set. This data set, based on historical data, include events. Hence, a performance evaluation to detect real sensor faults and quality events can be performed as we will show in the results.

Note that calibration and validation stages use independent data sets to avoid common problems when fitting a model (e.g. over-fitting).

As mentioned above, in the pre-processing stage, we first remove the outliers from the hourly observations $y(t)$ collected by the WU. We define an outlier as any observation more than three times interquartile ranges (IQRs) above the third quartile.

The next step standardizes the data with Z-score scaling of each quality parameter observed:

$$Z(t) = \frac{y(t) - \bar{y}}{\sigma} \tag{2}$$

The resulting signal has null mean and one as standard deviation. Then, a moving average with a sliding window of length n is applied to filter the noise:

$$S(t) = \frac{Z(t) + Z(t-1) + \cdots + Z(t-n-1)}{n} \tag{3}$$

Finally, the difference between observations are computed (i.e. differencing) to make each time series stationary:

$$Y(t) = S(t) - S(t-1) \tag{4}$$

In this work, we have considered two type of models to characterize the quality time series. On the one hand, the Time Series Models (TSM) capture the temporal redundancy. In particular, we consider in this work the Holt-Winters method (Winters, 1960), the Multivariate Differences algorithm (MV) (Mckenna et al., 2008) and an Artificial Neural Network (ANN) trained with historical data to forecast observations (Palani et al., 2008).

On the other hand, Spatial Models (SM) express the relations between sensors hydraulically related. For instance, a sensor located in the water distribution network should not observe an increase of the chlorine concentration if this event is not observed first by the sensor located in the tank.

Note that this rule makes the assumption that the reference sensor (placed in the tank) is more reliable than the sensor placed in the distribution network. This is a fair assumption given that the WU installs high-end chlorine analyzers in tanks and more common quality sensors in the distribution network.

3.2. Time Series Models

The time series model based on Holt-Winters (Winters, 1960) method for a time series with length L is

$$\hat{y}(t+h) = a(t) + h \cdot b(t) + s(t-p+1+(h-1)\cdot mod(L)), \tag{5}$$

where $a(t)$, $b(t)$ and $s(t)$ are updated by

$$\begin{aligned} a(t) &= \alpha \cdot (y(t) - s(t-L)) + (1-\alpha)\cdot(a(t-1)+b(t-1)) \\ b(t) &= \beta \cdot (a(t) - a(t-1)) + (1-\beta)\cdot b(t-1) \\ s(t) &= \gamma \cdot (y(t) - a(t-1) - b(t-1)) + (1-\gamma)\cdot s(t-L) \end{aligned} \tag{6}$$

where the parameters α, β and γ are obtained by minimizing the squared one-step prediction error using the training data.

Thus, a TS model $\hat{Y}_s^p$ is obtained per each water quality parameter p observed for each sensor s. The following residual from the measured signal and the prediction allows to detect changes:

$$r_{TS}(t) = \hat{Y}(t) - Y(t) \tag{7}$$

The Multivariate Distance algorithm (Mckenna et al., 2008) allows to detect changes in a group of parameters. In this work, the group of parameters are the observed by each multi-parameter device. The MV is expressed as:

$$r_{MV}(t) = \sqrt{\sum_{j=1}^{n} \left[Y_j(t) - \bar{Y}_j\right]^2} - \sqrt{\sum_{j=1}^{n} \left[Y_j(t-1) - \bar{Y}_j\right]^2} \tag{8}$$

where $\bar{Y}_j$ is the mean value of the parameter j.

Artificial Neural Networks (ANN) have been widely used in modelling time series in water networks as e.g. the water demands (Wu et al., 2014). In Palani et al. (2008), ANNs are used to learn existent linear and non-linear relationships between factors from water quality data in order to forecast these variables. In Sun (2013), ANN models are developed to predict groundwater level changes using a set of predictors: previous precipitation, terrestrial water storage change and maximum and minimum temperatures. In Valipour et al.

(2013), the goal is forecasting the inflow to Dez dam reservoir using ANN, Auto Regressive Moving Average (ARMA) and Auto Regressive Integrated Moving Average (ARIMA) models, identifying that the ARMA and ARIMA models perform better to forecast the inflow for the next 12 months and ANN models peform better to forecast the next 5 years. In Valipour (2016), three different structures of artificial neural network, the non-linear autoregressive neural network (NARNN), the non-linear input-output (NIO) and the NARNN with exogenous input (NARNNX) are compared forecasting the precipitation in Gilan to detect drought and wet year alarms.

The ANN is a set of units (neurons) connected to each other. These units are organized in three layers. The *input layer* are the units that receives the inputs from the outside, the *output layer* with units that generate the outputs to the outside and the *hidden layer(s)* with hidden units that links the input layer and the output layer via weighted connections. Here, we train an ANN to forecast chlorine at time t, as a regression model. Thus, the output layer is composed by only one node. The inputs of the ANN are the previous chlorine observations $\hat{y}(t) = f(y(t-1), y(t-2), \ldots, y(t-N))$. The residual is expressed as follows

$$r_{ANN}(t) = \hat{y}(t) - y(t) \tag{9}$$

Figure 4 shows the resulting ANN with the twelve inputs (I1, I2, ..., I12), the hidden layer with three hidden units (H1, H2 and H3), the output layer with one unit (O1), and B1 and B2 are bias layers that apply constant values to the nodes, similar to intercept terms in a regression model. The black lines are positive weights and the grey lines are negative weights.

The number of input units and hidden units have been obtained evaluating different set of parameters and selecting the model with minimal root-mean-square error (RMSE) defined as follows

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n} (\hat{y}(t) - y(t))^2}{n}} \tag{10}$$

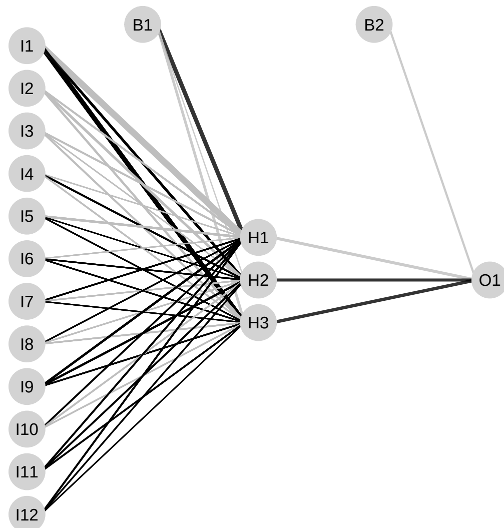

Figure 4: The resulting ANN to forecast chlorine observations (the output neuron O1) using previous observations (the input neurons I1, I2, ..., I12) using a single hidden layer with 3 units (H1, H2 and H3). Dark links indicate stronger relations (i.e. higher weighs) and light links weaker relations (i.e. lower weighs).

3.3. Spatial Models

Two spatial relations are considered in this methodology: the predecessor rule (PD) and the divergence measure (DV).

As mentioned before it is not possible to observe an increase of the chlorine concentration at the sensor $Y_s(t)$, placed in a demand sector, if this event is not observed first by the sensor $Y_r(t)$, located in the tank. This simple statement is expressed in the following relation using the standardization process (2):

$$Z_s(t) \leqslant Z_r(t) \tag{11}$$

Hence, the residual of the PD can be formulated as follows

$$r_{PD}(t) = (Z_r(t) - Z_s(t))^2 \tag{12}$$

This residual is first evaluated in normal conditions (without faults) to establish a threshold. Hence, we can compare the residual computed online against the threshold to detect a divergence between a reference sensor r and a spatially linked sensor s.

Furthermore, there are hydraulic configurations presenting various sensors spatially related. In this situation, the observations collected of a same magnitude from different sensors should converge. Thus, we can generalize (12) to measure the convergence between various hydraulically linked sensors:

$$r_{DV}(t) = \sum_{j=1}^{N}(Z_s(t) - Z_j(t))^2, j \neq s \tag{13}$$

It must be noted that the conclusions obtained from this model will be wrong or meaningless if two or more sensors are observing inaccurate data at the same time. For this reason, this model is discarded from the methodology.

3.4. Fault Diagnosis

Using any of the proposed models alone, it will be only possible to detect that something unexpected, based on the historical knowledge, has occurred. However, it will not be possible to distinguish if the problem is a sensor fault or a quality event.

In particular, the Holt-Winters TSM, MV and ANN models are able to detect unexpected changes in the quality parameters signal, but they do not allow to determine if the change produced is a real change in the water quality parameters or, if actually it is due to inaccurate data collected from a sensor affected by some problem. Hence, spatial information is required to contrast the events detected against additional information provided by other sensors related.

Thus, the spatial models, DV and PD, are considered to provide this additional information.

Furthermore, some of the temporal models presented in the previous section are redundant regarding our goals. For instance, the MV, Holt-Winters and ANN detect abrupt changes in the behaviour of the quality measurement signal. A comparison among them will be presented in order to select the one that presents a better detection performance. Analogously, the spatial-based models, PD and DV, track the dissimilarity with respect to other sensors spatial-related. Again, after comparing them, the one that provides best detection performance is selected.

Combining all this knowledge, a fault diagnosis scheme is developed to interpret the combination of the results and provide the key indicators to the WU to improve and anticipate the sensors maintenance operations.

Each model-based residual are *binarized* in the detection test, i.e. the test generates a 1 if the residual is within the model threshold and 0 otherwise. The lower bound θ_x^{LB} and upper bound θ_x^{UB} for (7) and (9) are estimated based on the following expression:

$$\begin{aligned}\theta_x^{LB} &= Q_1 - 3 \cdot IQR_x \\ \theta_x^{UB} &= Q_3 + 3 \cdot IQR_x\end{aligned} \tag{14}$$

where Q_1 and Q_3 are the first and third quartiles respectively, and IQR_x is the interquartile range (difference between the third and first quartiles) obtained from the residuals of the validation data set.

The upper bound of (12) (notice that the residuals are squared) is

$$\theta_x^{UB} = C \cdot \max(r_x) \tag{15}$$

where C is the constant that defines the sensitivity of the model and $r_x \in \{r_{DV}, r_{PD}\}$ using the validation data set.

The fault diagnosis system can be formalized as a discrete-event system. Figure 5 presents the state diagram. From the normal state there are two possible outcomes: a quality event or a sensor fault. When a sensor fault is detected, a maintenance operation is performed. A quality event can be caused by an intended action (e.g. hydraulic action, chlorine reference change) or by some unexpected infiltration.

The states are characterized in the Table 2 as a function of the activation of model-based tests, except the calibration state which is clearly known by the WU maintenance department.

As detailed in Table 2, a sensor is in normal state when all the tests are not active. A quality event is diagnosed when PD test is not active and ANN is

Table 2: Fault signatures based on the models residuals.

PD	ANN	$\overline{PD} \wedge$ ANN	Cause
1	1	0	Distribution sensor fault
1	0	0	Distribution sensor fault
0	1	1	Quality event
0	0	0	Normal state

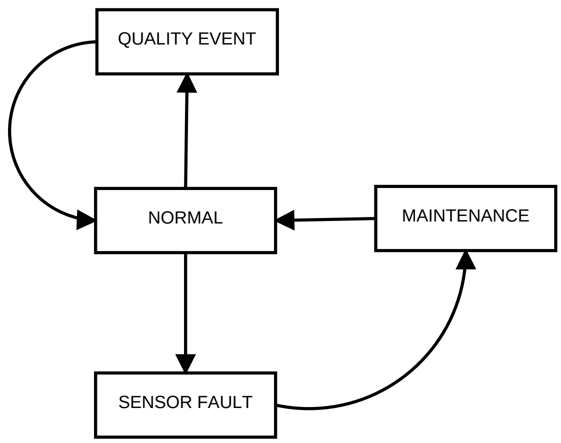

Figure 5: State diagram of a quality sensor.

active. When PD test is activated, a sensor fault is diagnosed, regardless of the ANN test.

4. Results

In this section, results based on the Barcelona case study detailed in Section 2 are presented next to show the performance of the methodology proposed in this work.

The data used to generate the results come from the multi-parametric (chlorine, pH, temperature and conductivity) sensors (0794, 0795 and 0801), the chlorine analyzer X127701D and the events reported by the WU experts to the maintenance department (map detailed in Figure 2).

The historical data of events allow us to analyze the performance of our diagnosis approach. The performance measure selected is the anticipation in days and the false alarms rate.

A 1-year data set has been divided in three independent subsets: a training set (one month of data) is used to calibrate the models, a validation set (fifteen days) is used to analyze how the model generalize with new data and finally a test set (seven months) is used to show the performance of each model detailed in Section 3. We assume that the training and validation sets have no events in order to characterize the system in a normal state (i.e. without faults).

A first scenario considering two chlorine measurement signals is shown in Figure 6. The solid black line corresponds to the chlorine sensor 0794 placed at a demand sector and the dotted black line is the analyzer X127701D placed at the reservoir where the chlorination process is done. The red vertical lines indicate the time instants of the events reported by the WU experts, based on their accumulated knowledge. There are five events reported in 1-year period of data. The first, third, fourth and fifth events show the most common problem with an online chlorine sensor: the sensitivity loss. This is caused by the degradation of the membrane and the electrolyte of the chlorine sensor. If we look closely, the patterns of the chlorine signals are pretty similar just before the events were reported: in a certain time instant, the chlorine signal decays while the transport sensor does not indicate any decay. The WU experts detect this event and report the event to the maintenance department to plan the corrective actions.

Figure 7a shows the first two months of raw data collected from the water demand sector presented in Figure 2—the three multi-parametric sensors of the distribution network with ids: 0794, 0795 and 0801; and the transport analyzer with the id X127701D—and Figure 7b shows the pre-processed data, i.e. without outliers, smoothed and standardized using the Z-score (see Section 3.1 for further details). The plots, stacked in vertical, are the set of parameters observed. From top to bottom are: conductivity (C) in μS/cm , chlorine (Cl) in mg/L, pH and temperature (T) in °C, respectively. This scenario corresponds to the first fault reported in Figure 6, i.e. the first vertical red line. As it can be seen, the chlorine signal of the sensor 0794 shows a slight drift along 20 days

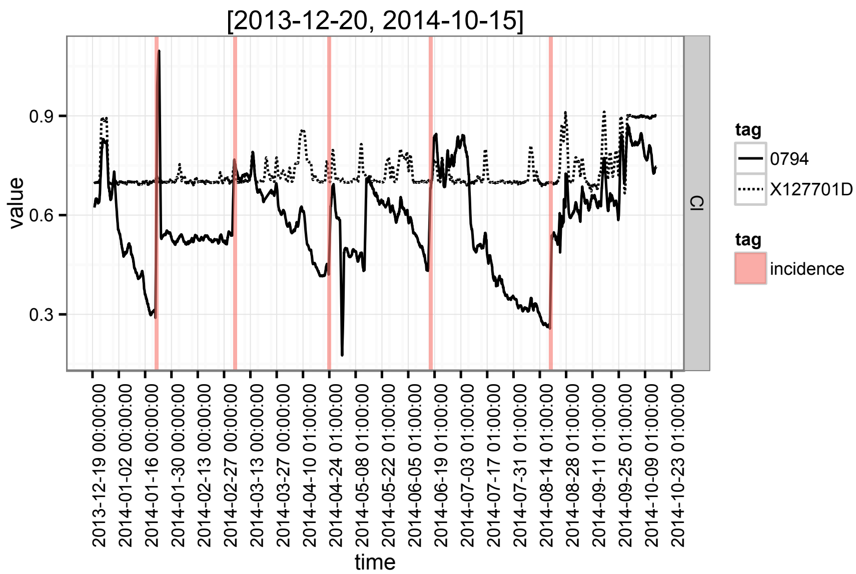

Figure 6: Chlorine signals from 0794 sensor and X127701D.

regarding the rest of chlorine sensors 0795, 0801 and X127701D. Moreover, as it can be noticed, there is a clear distance between its pH signal against 0795 and 0801 pH signals.

This particular scenario was detected and fixed by the WU as follows. On the 21 of January in 2014, the quality water data analyst, in a check routine, detects a slow chlorine decay of the 0794 compared against the other two sensors (0795 and 0801) and to the transport sensor (X127701D). Once noticed the problem, the water quality analyst reported the event to the maintenance department. Afterwards, on the 22 of January, a maintenance technician makes a readjustment in order to recalibrate the sensor. Due to this operation, the sensor 0794 shows an abrupt increase of the chlorine, and a decrease of pH at the same time, during two days (since 22 to 24 of January), and after this period it converges again.

Figure 8a shows the residuals of the models (detailed in Section 3). Figure 8b shows the binarized residuals (a binarized residual is 1 if exceeds the model's threshold and 0 otherwise, see Section 3.4 for further details) to visualize clearly when a residual exceeds the detection threshold. The ANN (top plot) detects the maintenance calibration operation (from 22 to 24 of January). But looking at the ANN binarized residual, it can be seen that it starts to detect something a day before the operation. The same happens with DV model, but it starts to detect something in 12 of January. Moreover, the HW and MV only detects the maintenance operation. These models, as mentioned before, are not capable of detect a slow degradation fault as in this case.

The PD model detects a divergence between the sensor 0794 and the transport analyzer X127701D since 15 of January. As it can be seen in Figure 8b, there is a sequence of two solid blocks: the first detection, from 15 to 21 of January, of the degradation fault and the second from 22 to 24 of January is the maintenance operation.

The models DV and PD perform in a similar way, detecting divergence between spatial related sensors are able to detect a drift fault. Moreover, the models HW and ANN detect abrupt changes but not a drift fault. And the MV model is the less sensitive model detecting extreme events, the peaks caused by the maintenance operation.

Figure 9 shows another scenario. This is a real quality event where the chlorine concentration is increased from 0.7 to 0.9. The resulting binarized residuals are shown in Figure 10. As we can see, the PD model does not detect any event, but the other models detect the change on the pattern of the signals caused by the new chlorine injection configuration.

Figures 11, 12 and 13 show the fault diagnosis of the chlorine sensors 0794, 0795 and 0801, respectively. And Tables 3, 4 and 5 show the diagnosis anticipation of our approach regarding the events reported by WU experts. Each row represents a sensor fault detection produced by our approach. The columns *start detection* and *end detection* are the date interval along our approach detects a sensor fault, the column *event reported* is the date when the WU expert detected the fault and *anticipation* in days of our approach regarding the event reported.

The rows with a blank in the event reported column, apparently false alarms, are motivated by two causes. On the one hand, the table shows only reported events, not planned maintenance operations (information not available). Thus, some events detected by our approach have been fixed in the maintenance operations before being detected and reported by the WU experts. For instance, Figure 13 shows a decay of the 0801 chlorine signal starting at the end of July till the end of August. At the end of August, an abrupt rise of the chlorine is caused by a planned maintenance operation. On the other hand, false alarms occur due to tight thresholds considered. For instance, the 0801 sensor fault detected at 2014-05-09 go on for one day only (does not appear in the bottom color bar of Figure 13 because of the short width).

With the approach presented in this work, we anticipated in 12.4 days, on average, the detection of a sensor problem before the fault was reported by the WU expert using knowledge accumulated with visual analysis.

Table 3: Fault detection, diagnosis and anticipation on sensor 0794

	start detection	end detection	event reported	anticipation (days)
1	2014-04-06	2014-04-22	2014-04-23	16
2	2014-04-27	2014-05-01		
3	2014-05-02	2014-05-11		
4	2014-06-11	2014-06-13	2014-06-16	5
5	2014-07-13	2014-08-19	2014-08-19	37
6	2014-08-22	2014-08-25		

5. Conclusions

This paper has proposed a methodology to detect water quality changes based on multi-parametric sensors. It has been shown that it is not possible looking at the different tests separately to distinguish between a sensor fault or

Table 4: Fault detection, diagnosis and anticipation on sensor 0795

	start detection	end detection	event reported	anticipation (days)
1	2014-03-11	2014-03-16	2014-03-17	6
2	2014-04-04	2014-04-07		
3	2014-05-24	2014-05-25	2014-05-27	3
4	2014-05-30	2014-06-09	2014-06-04	5
5	2014-06-20	2014-06-26		
6	2014-07-18	2014-08-10	2014-08-11	23
7	2014-08-27	2014-09-04	2014-09-02	5
8	2014-09-12	2014-09-21	2014-09-23	10

Table 5: Fault detection, diagnosis and anticipation on sensor 0801

	start detection	end detection	event reported	anticipation (days)
1	2014-03-16	2014-03-18		
2	2014-03-28	2014-04-07	2014-04-07	9
3	2014-04-11	2014-04-27	2014-04-28	17
4	2014-05-09	2014-05-09		
5	2014-05-22	2014-05-24		
6	2014-05-28	2014-06-01		
7	2014-06-02	2014-06-14	2014-06-16	13
8	2014-07-31	2014-08-03		
9	2014-08-05	2014-08-10		
10	2014-08-11	2014-08-25		
11	2014-09-04	2014-09-05		
12	2014-09-12	2014-09-25		
13	2014-09-28	2014-09-29		
14	2014-10-01	2014-10-11		

an actual quality event. A fault diagnosis algorithm has been developed able to distinguish between water quality events and problems affecting the sensors such as loss of sensitivity.

This approach has been applied to the Barcelona Water Network and the results obtained show that the methodology detailed is able to anticipate the detection of future problems in chlorine sensors compared to the visual analysis applied by WU experts. Hence, the proposed approach improves the water quality control management and reducing corrective maintenance actions. As a future research, it is planned to integrate the hydraulic model in the methodology in order to reduce the uncertainty of the methodology and extend the proposed methodology to predict the degradation of the sensors and to plan the maintenance according the sensors' health.

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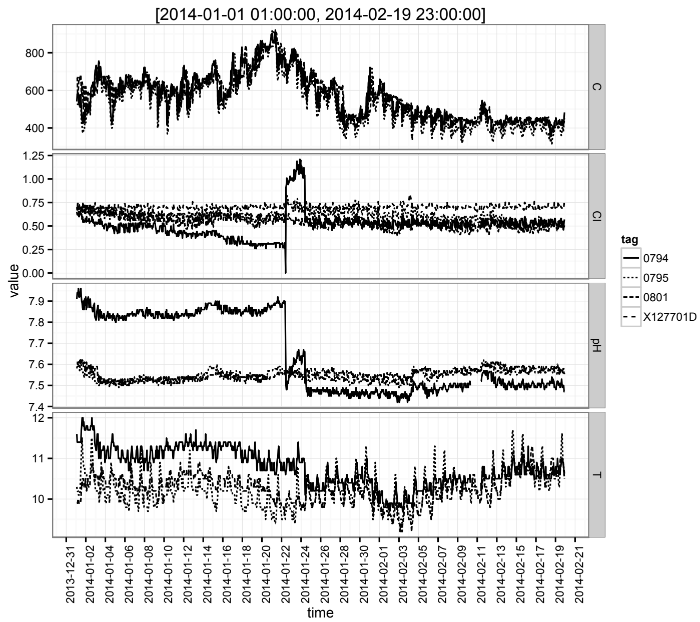
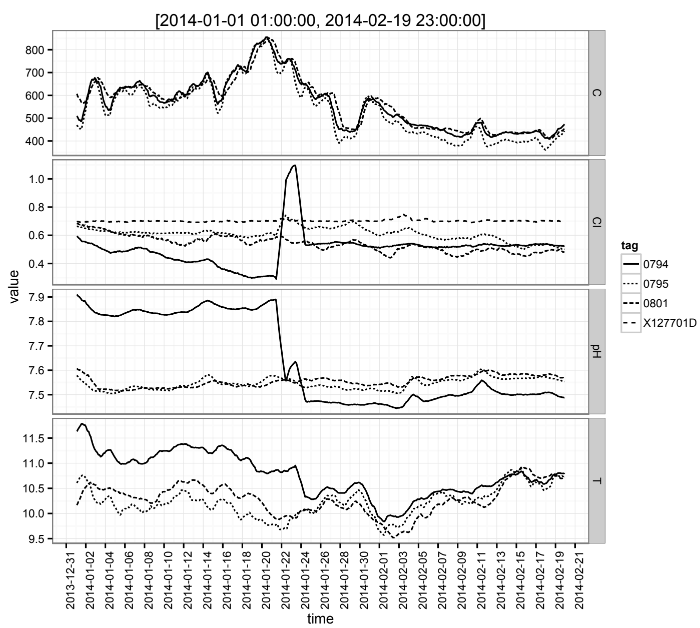
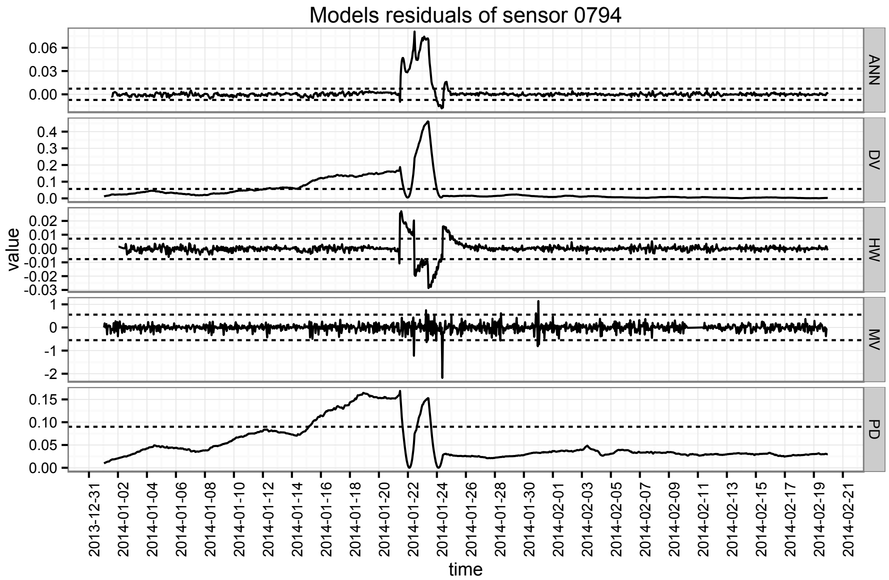


(a) Raw observations.

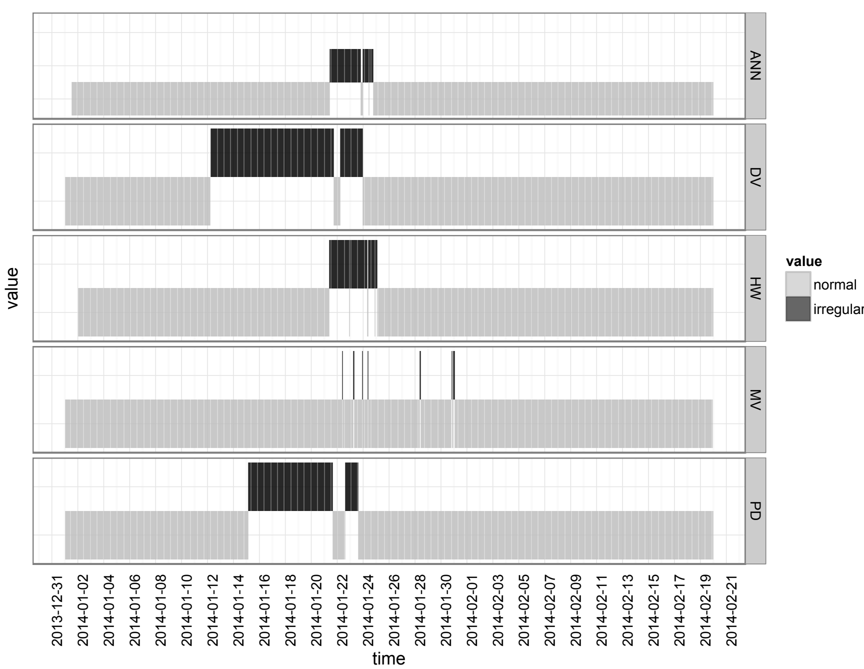


(b) Pre-processed observations.

Figure 7: Stacked plots (by quality parameter) from the three multi-parameter quality sensors and the chlorine analyzer.



(a) Residuals of the models.



(b) Binarized residuals of the models.

Figure 8: Models' residuals of the first chlorine event of sensor 0794.

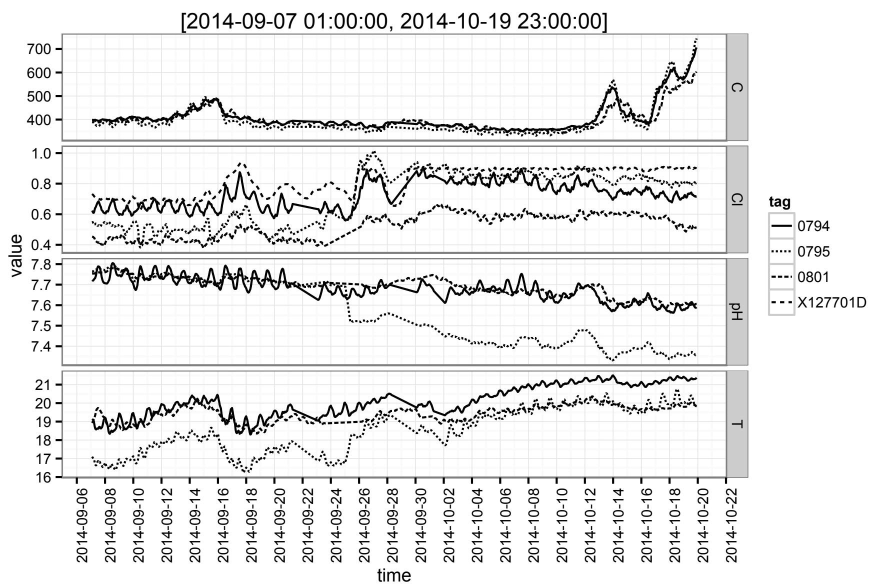


Figure 9: Stacked plots (by quality parameter) of the pre-processed observations from the three quality sensors during a chlorine set point change.

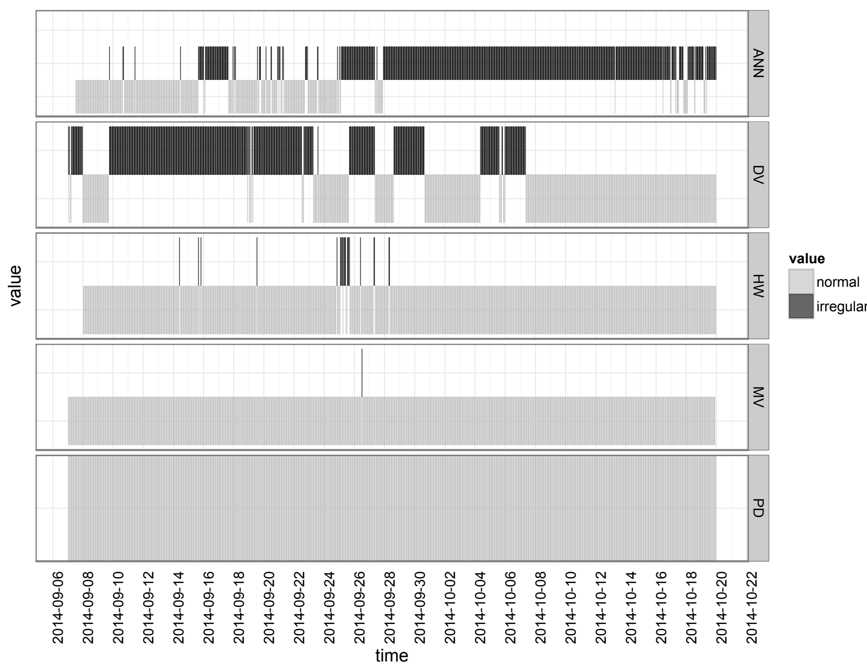


Figure 10: Binarized residuals of the models during a chlorine set point change.

Figure 11: Chlorine signals from 0794 sensor and X127701D and fault diagnosis.

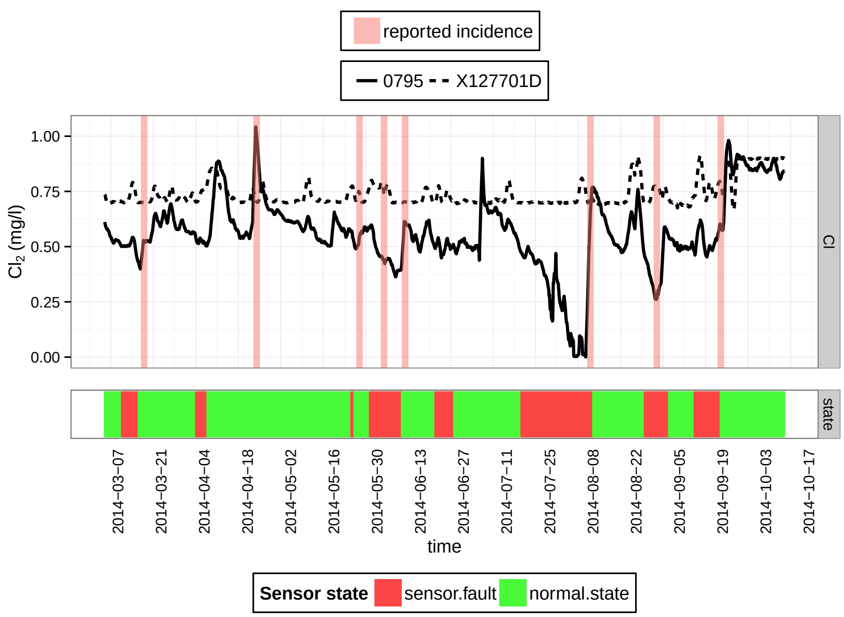


Figure 12: Chlorine signals from 0795 sensor and X127701D and fault diagnosis.

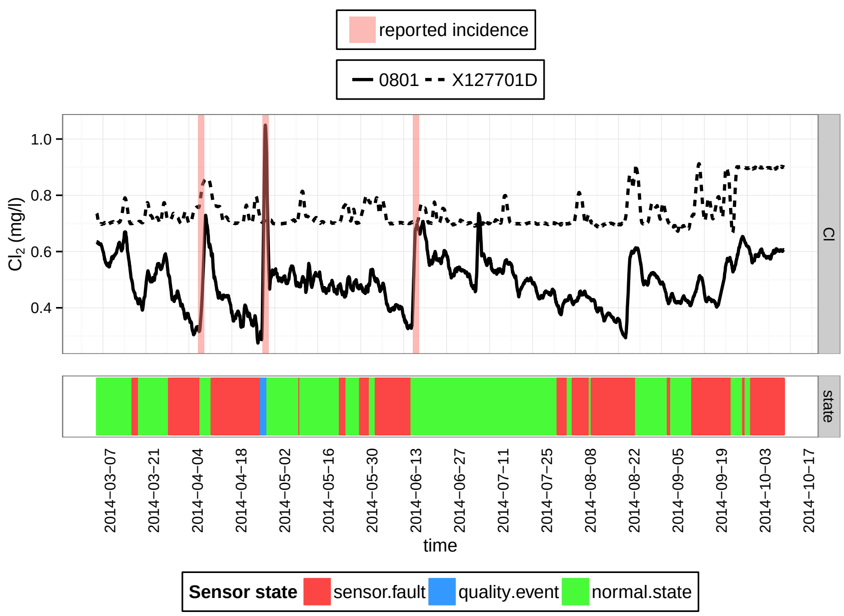


Figure 13: Chlorine signals from 0801 sensor and X127701D and fault diagnosis.

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